# Routing Optimization of Electric Vehicles for Charging with Event-driven Pricing Strategy

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***Abstract*****—**With the increasing market penetration of electric vehicles (EVs), the charging behavior and driving characteristics of EVs have an increasing impact on the operation of power grids and traffic networks. Existing research on EV routing planning and charging navigation strategies mainly focuses on vehicle-road-network interactions, but the vehicle-to-vehicle interaction has rarely been considered particularly in studying simultaneous charging requests. To investigate the interaction of multiple vehicles in routing planning and charging, a routing optimization of EVs for charging with an event-driven pricing strategy is proposed. The urban area of a city is taken as an case for numerical simulation, which demonstrates that the proposed strategy can not only alleviate difficulties for EV fast charging but also improve the utilization rate of charging infrastructures.

***Note to practitioners-*** This paper was inspired by the concerns of difficulties for EV's fast charging and the imbalance of the utilization rate of charging facilities. Existing route optimization and charging navigation research are mainly applicable to static traffic networks, which cannot dynamically adjust driving routes and charging strategies with real-time traffic information. Besides, the mutual impact between vehicles is rarely considered in these works in routing planning. To resolve the shortcomings of existing models, a receding-horizon based strategy that can be applied to dynamic traffic networks is proposed. In this paper, various factors that the user is concerned with in the course of driving are converted into driving costs, through which each road section of traffic networks is assigned the corresponding values. Combined with the graph theory analysis method, the mathematical form of the dynamic traffic network is presented. Then, the paper carefully plans and adjusts EV driving routes and charging strategies. The simulation case demonstrates that the proposed method can significantly reduce the difficulty for EV fast charging while alleviating unreasonable distributions of regional charging demand.

***Index Terms*****—**electric vehicle, event-driven, routing optimization, navigation, receding-horizon.

## I. Introduction

With the continuous increase of vehicle uptake, the demand for oil consumption has increased dramatically in recent years, making energy scarcity problems and environmental pollution increasingly serious [1]-[3]. To address it, many governments worldwide are actively promoting the application of EVs, whose large-scale popularization is bound to become a trend. With the increasing penetration of EVs, two main concerns emerge [4]-[5]: 1) The growth scale of EV penetration is significantly higher than that of charging infrastructure, expanding the gap between the twomaking it difficult to charge quickly on road, and aggravating the mileage anxiety of EV users; 2) The driving and charging characteristics of a large number of EVs will bring certain problems to power grids and traffic systems, such as unbalanced charging load, traffic congestion, etc. The two concerns highlight the importance of adopting effective charging scheduling strategies to plan optimal routing and recommend reasonable charging stations [6]. This can not only reduce the mileage anxiety caused by battery capacity constraint, but also reduce the impact of EV driving and charging characteristics on power grids and traffic networks. The abundant literature that address these concerns can be divided into three main categories.

The first category of literature mainly focuses on constructing and developing intelligent transportation systems by integrating advanced information, data communication, electronic sensors, and electronic control technologies [7-12]. Ref. [7] investigated and analyzed the development and research in ITS and proposed valuable insights into the current status and future development of ITS technologies. Ref. [8-10] outlined various challenges and open questions in ITS and discussed solutions for EV mobility, traffic control, traffic prediction, parking with the method of crowd intelligence, deep reinforcement learning, big data, etc. respectively. In [11], an efficient multi-metric routing protocol for ITS was proposed, which considered five metrics: link capacity, connectivity, Euclidean distance, relative velocity, and end-to-end delay to maximizing the packet delivery ratio (PDR) while minimizing the delay of the network. To improve the energy utilization of ITS, a dynamic and intelligent traffic light control system was proposed in ref. [12]. Real-time traffic information was used to dynamically adjust the on-ff durations of traffic lights. Above studies focus on a specific area of the development and application of ITS, and they did not consider the combined application of EVs and power grids. Different from them, this paper proposes a combined application model of ITS with EVs and power grids for EV routing and charging navigation.

The second category of literature concentrated on addressing the optimal routing and charging problems of individual EV users or a large population of EVs, considering charging time, constraint of energy stored in the battery, and mileage anxiety, etc. [13-17]. Author [13] proposed an optimal routing strategy for EVs with minimal travel time cost and energy cost as well as the number of EVs that were dispatched. A regional hierarchical charging control framework was proposed in [14], which satisfied the charging demand of EVs,

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and reduced the peak load of distribution networks and the operation cost of charging stations. The traffic flow and driving speed in traffic networks were assumed to be constant in the above literature, but in reality, they change under the complex and varying traffic conditions. To avoid the depletion of all battery power and ensure the safe operation of EVs in driving, a dynamic Dijkstra algorithm with some improvements compared with the traditional algorithm was adopted to search for the most energy-saving paths for charging in [15]. A two-stage method to compute optimal routing time for EVs was proposed in [16], where the multi-objective shortest routing problem was solved through the adaptive Moore-Bellman-Ford algorithm. To meet the welfare of all passengers while maximizing the energy efficiency of transit service providers, an optimal routing and charging framework was proposed for high-efficiency dynamic transit systems, which considered energy efficiency and charging price [17]. All these papers on optimal routing and charging of EVs mainly focuses on the interaction between EVs, traffic networks and power grids. However, the driving routing and charging choice of EVs can also affect each other. If the multi-vehicle interactions between EVs are ignored, the routing and charing results could dramatically deviate from the actual situation.

The third category of work mainly studies the impact of electricity price incentives on EV driving and charging characteristics. As a movable load, EV has flexible demand response characteristics in space scope. A reasonable charging strategy was conducive to reducing travel costs while improving the utilization of charging infrastructure [18-22]. Considering the total revenue of charging stations and the response of users to charging prices, the pricing strategies of charging stations were optimized to minimize the voltage deviation of distribution networks in [18]. A pricing-based control method was adopted in [19], through which EV charging demand could be transferred from peak hours to non-congestion periods, relieving congestions at charging stations. In [20], a threshold-based pricing strategy was proposed, which considered queuing time at the charging station and the profits of charging network operators (CNO) with a flat-rate charging price. Paper [21] proposed an incentive-compatible pricing and routing strategy, through which EV charging was guided to maximize social welfare or CNO's profits. Ref. [22] introduced a charging price strategy that distinguished the busyness of charging stations, motivating users to adjust charging time to improve the utilization of charging infrastructure and reduced the waiting time at charging stations. In [23-24], a scheduling strategy was proposed to charge multiple vehicles through matching with intermittentt renewable generation while minimizing the total charging cost and. Paper [25] proposed an appointment-based mobile charging scheduling strategy to provide an economical and efficient EVs charging service. It can schedule optimal mobile chargers for EVs with reservations. The above studies design pricing strategies that only consider a certain factor concerning users. However, different types of users are concerned with different factors when choosing driving routing and charging strategies. For this reason, only some users are willing to accept the navigation, which makes these strategies unable to achieve the expected effect in the actual application.

Apat from above three categories of studies, the reasonable location planning of charging stations was also one measure to alleviate the difficulty of EV's rapid charging and uneven distributions of charging load [26-28]. Ref. [26] proposed a method to determine the optimal electrical access points of charging stations so as to reduce the risk of distribution network operation caused by EV charging loads. The semi-invariant and Gram-Charlier series was adopted to calculate the dynamic probability power flow of distribution networks. Considering the comprehensive profits of charging station operators, EV users, and the power grid, a sitting and sizing planning model for charging stations was proposed in [27], solved by the chaos simulated annealing particle swarm optimization algorithm. Further considering EV ownership growth and the uncertainty of EV growth rate, H. Zang et al. proposed a stochastic chance-constrained dynamic programming for charging stations in [28]. In above papers, charging station location planning was modeled based on the distributions of EV charging load but without navigation strategies, which means charging loads were disorderly distributed. With the improvement of internet of vehicles (IoV) platform, EV driving routes and charging choices with intelligent navigation systems would be more orderly and appropriate, making current research not necessarily applicable in practice.

To fill the aforementioned research gap, a routing optimization of EVs for charging with an event-driven pricing strategy is proposed in this paper. Specifically, an intelligent navigation framework based on multi-network interaction is first established. It is then used to explore the information interactive relationship between EVs, charging stations, intelligent transportation systems (ITSs), and information processing centers (IPCs) for EV routing and charging navigation. Thereafter, by combining the speed-flow model and speed-energy consumption model a comprehensive road impedance model, is proposed to reflect the all-day comprehensive travel cost of each road section. The model considersvarious factors, including the length of the road section, driving time, energy consumption, etc., which concern users . Then, considering the impact of multi-vehicle interaction between EV charging, an event-driven charging service pricing model and priority reservation cost mechanism are proposed. Thereafter, a receding-horizon based optimal routing method is proposed to overcome the static shortcomings of traditional search algorithm. It recommends optimal routing according to the real-time information of traffic networks. Finally, based on the distributions of EV charging demand under the proposed navigation strategy, new charging stations are planned to further reduce the charging cost of users, while balancing the utilization between charging stations. The numerical simulation on the urban areas of a selected city is conducted to illustrate the effectiveness of the proposed method.

The main contributions of this paper are as follows:

- Considering the impact of multi-vehicle interactions between EV charging, an event-driven pricing strategy for charging station charging service fee is proposed. It adjusts the charging price dynamically through the occurrence of events of EV request for charging, arriving or leaving the charging station. This pricing strategy closely contacts time and price, making the shortest queuing time and the lowest charging price compatible in charging navigation.

- A priority reservation cost mechanism is proposed to implement an orderly reservation between EVs that request for charging simultaneously.
- A comprehensive road impedance mode is proposed to reflect all-day comprehensive travel cost of each road section, considering various factors including the length of the road section, driving time, energy consumption, etc. concerned by users..
- Based on the distributions of EV charging load with the navigation strategy proposed in this paper, the location of new charging stations are planned in the traffic network. Its rationality is proved by the numerical study in Section V prove.

The rest of the paper is organized as follows: Section II gives a short description of the navigation system with the multi-network interaction. Section III describes the model of dynamic traffic. In Section IV, the modeling approach for routing navigation and charging service pricing for EV is presented. Test studies are presented in Section V, and conclusions are drawn in Section VI.

## II. Intelligent Navigation Framework

With the gradual networking and commercial use of 5g communication, the application of intelligent communication technology (ICT), intelligent transportation system (ITS), etc., in vehicle-road collaboration has become increasingly mature. Edge computing technology [29] provides users with a high reliability and low delay operating environment. It could also reduce the computing load of central scheduling nodes, enabling information between EVs-charging stations-ITS-information processing center (IPC) sharing and transmission. To coordinate the information exchange of planning EV driving routes and charging navigation, this paper proposes an intelligent system framework, which contains four modules, as shown in Fig.1. The functions of each module are as follows:

- IPC is the control center of the system, which is assumed to be a non-profit and socially regulated agency in this framework. It plans the charging scheduling strategies by combining the information uploaded by other modules.
- ITS mainly provides real-time traffic information for IPC for planning routing and charging navigation. The traffic condition directly constrains the driving speed, driving time, and energy consumption of EVs in driving.
- Charging stations provides charging services for EVs and upload the facility utilization information to IPC. As charging facilities, the location, busyness, charging price directly affects the charging strategy for EV users.
- As the user of this intelligent system, the charging decisions of EV drivers directly determine the degree of congestion at charging stations and in turn affect the charging decisions of other users.

Then, the entire navigation process for EV routing and charging can be described as follows：

After receiving EV navigation requests, the IPC plans the driving routing and charging strategy for EVs in combination with real-time traffic information and facility utilization information uploaded from ITS and charging stations respectively. Thereafter, the user decides whether to accept the navigation strategy and feedback the decision to the IPC. Finally, the IPC reserves charging for the driver at the corresponding charging station according to the decision, and feeds back the routing and charging strategy to ITS and charging stations respectively for updating information.

To simplify calculations, communication delays, and the time consumed to plan a driving route and charging strategy are ignored in the entire navigation process.

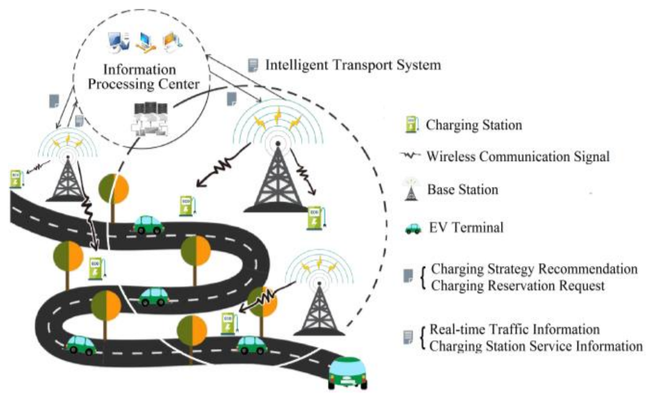


Fig. 1. Navigation system framework

## III. Dynamic Traffic Network Model

The mathematical model of traffic networks is described through graph theory in this section firstly. Then, by introducing the speed-energy consumption and speed-flow model, the road impedance model and dynamic traffic network model are proposed, which help model routing planning and charging navigation.

### A. Road Topology

The traffic network model is the basis for routing planning and charging navigation. The topology of the traffic network is shown in Fig.2. Graph theory [30] is adopted to model the traffic network.

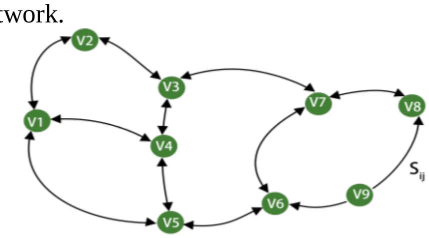


Fig. 2. Traffic network topology

$R_n = (V, E, S)$ represents the traffic network, where $V$ is the set of all road intersections, $E$ is the set of all connected road sections and $S$ is the set of road weight, i.e. the road impedance in the traffic network.

The weight matrix $S$ of the traffic network in Fig.2 can be expressed as follows by quantitatively evaluating the traffic network with direction and weight,

$$S=\begin{bmatrix} 0 & s_{12} & \infty & s_{14} & s_{15} & \infty & \infty & \infty & \infty \\ s_{21} & 0 & s_{23} & \infty & \infty & \infty & \infty & \infty & \infty \\ \infty & s_{32} & 0 & s_{34} & \infty & \infty & s_{37} & \infty & \infty \\ s_{41} & \infty & s_{43} & 0 & s_{45} & \infty & \infty & \infty & \infty \\ s_{51} & \infty & \infty & s_{54} & 0 & s_{56} & \infty & \infty & \infty \\ \infty & \infty & \infty & \infty & s_{65} & 0 & s_{67} & \infty & s_{69} \\ \infty & \infty & s_{73} & \infty & \infty & s_{76} & 0 & \infty & \infty \\ \infty & \infty & \infty & \infty & \infty & \infty & s_{87} & 0 & s_{89} \\ \infty & \infty & \infty & \infty & \infty & s_{96} & \infty & s_{98} & 0 \end{bmatrix} \quad (1)$$

where $s_{ij}$ is the element of matrix $S$. It's noted that if $v_i = v_j$, $s_{ij}$=0; if $e_{ij} \notin E$, $s_{ij}$=∞.

### B. Comprehensive Road Impedance Model

In traffic network $R_n = (V, E, S)$, road impedance $s_{ij}$ is the travel cost of a road user through a certain section, which can be quantified by the length of the road section, the speed of traffic, the travel time, etc.

Currently, the length of the road section is usually used as the road impedance in the traffic network model. However, the length of a road section is a fixed quantity that does not change with traffic conditions, which cannot reflect the dynamic and changeable characteristics of urban traffic networks. BY Using road length as road impedance to navigate EVs, the recommended road is single, prone to traffic congestion. However, the dynamic road impedance, such as travel speed and travel time, can only reflect a certain aspect of user travel concerns but not comprehensive. To address these issues, a road impedance model based on the comprehensive travel cost is proposed in this paper, considering the length of road section, driving time, energy consumption, and other factors.

To quantify the comprehensive cost with different traffic conditions, the speed-flow model [31] and the speed-energy consumption model [32] are introduced for modeling analysis.

In urban traffic networks, the driving speed of EVs is mainly affected by road capacity and traffic flow. According to [31], the driving speed $\bar{V}_{ij}(t)$ of EV at time $t$ on a directly connected road section $e_{ij}$ can be expressed as:

$$\bar{V}_{ij}(t) = \frac{\bar{V}_{ij}^{free}}{1+\left(\frac{q_{ij}(t)}{C_{ij}}\right)^{\beta}} \quad (2)$$

$$\beta = a + b\left(\frac{q_{ij}(t)}{C_{ij}}\right)^{n} \quad (3)$$

where $\bar{V}_{ij}^{free}$ indicates the free-flow speed of road section $e_{ij}$, $C_{ij}$ is the capacity of a road section $e_{ij}$, $q_{ij}(t)$ is the traffic flow of road section $e_{ij}$ at time $t$, the ratio of $q_{ij}(t)$ and $C_{ij}$ is the road saturation at time $t$, $a$ , $b$, $n$ are adaptive coefficients at different road levels, which can be obtained from the experimental data in ref [31]. The roads are divided into an urban expressway, main roads, and secondary roads in our model.

EV energy consumption prediction is also a key content of charging routing planning. In urban transportation networks, the unit energy consumption mileage of EVs varies greatly under different traffic conditions [15], [33-35]. To reflect the relationship between energy consumption and driving speed, a speed-energy consumption model based on measured data of EVs is adopted [32].

$$\begin{cases} \Delta E_f(t) = 0.247 + \frac{1.52}{\bar{V}_{ij}(t)} - 0.004\bar{V}_{ij}(t) + 2.992\times 10^{-5}\bar{V}_{ij}(t) \\ \Delta E_m(t) = -0.179 + 0.004\bar{V}_{ij}(t) + \frac{5.492}{\bar{V}_{ij}(t)} \\ \Delta E_{se}(t) = 0.21 - 0.001\bar{V}_{ij}(T_i) + \frac{1.531}{\bar{V}_{ij}(t)} \end{cases} \quad (4)$$

where $\Delta E_f(t)$, $\Delta E_m(t)$, $\Delta E_{se}(t)$ are energy consumption unit mileage in urban expressways, main roads, and secondary roads.

Then, the driving time and energy consumption of the EV on-road section $e_{ij}$ can be calculated as:

$$t_{drive,ij} = \frac{e_{ij}}{\bar{V}_{ij}(t)} \quad (5)$$

$$p_{loss,ij} = e_{ij}\Delta E_{ij}(t) \quad (6)$$

The impedance model of a section $e_{ij}$ is:

$$s_{ij} = \theta t_{drive,ij} + \eta p_{loss,ij} \quad (7)$$

where $\theta$ is the unit time cost coefficient, $\eta$ is the unit electricity price of the EV for last charging.

Let the time intervals in which the user's travel rules and traffic conditions are similarly divided into the same period. The proposed dynamic traffic network model is:

$$R_{\breve{n}} = (V, E, T, S) \quad (8)$$

where

$$V = \{v_i |\ i = 1, 2, \dots, n\} \quad (9)$$

$$E = \left\{e_{ij} \middle|\ v_i \in V, v_j \in V, v_i \neq v_j\right\} \quad (10)$$

$$T = \{t_i |\ i = 1, 2, \dots, n\} \quad (11)$$

$$S = \left\{s_{ij}^{t_i} \middle|\ e_{ij} \in E, t_i \in T\right\} \quad (12)$$

where $T$ is the time series set. The day is divided into $n$ periods, and the update frequency is $t_{i+1} - t_i$.

## IV. Routing And Charging Navigation Strategy

The receding-horizon based optimal routing method is firstly introduced for EV routing planning without charging demand in subsection IV.A. Then, a single EV model with charging demand is taken as an example to describe the event-driven charging service pricing strategy in IV.B. It contributes to modeling charging navigation strategy presented in subsection IV.C, combined with the method in IV.A. Based on subsections IV.A-C, the charging navigation strategy of EVs considering multi-vehicle interactions is described in subsection IV.D. The overall framework of Section IVis shown in Fig.3.

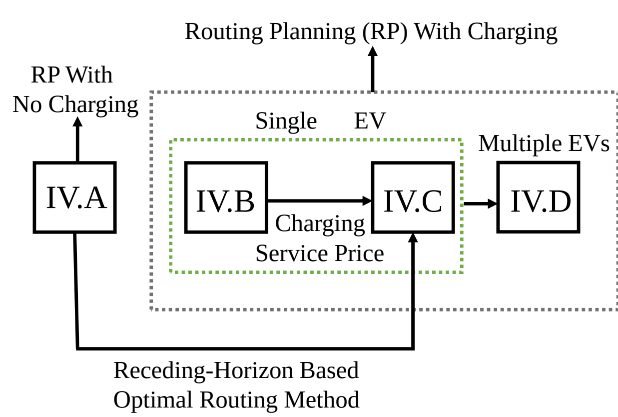


Fig. 3. Overall framework of Section IV

### A. Routing Planning With No Charging

*1) Problem Description*: The origin $v_i$ and destination $v_j$ of EV at time $t$ can be obtained by OD analysis [36], while there are usually multiple routes in the traffic network from $v_i$ to $v_j$ for users. The route with the lowest comprehensive cost between $v_i$ and $v_j$ can be obtained by searching traffic network impedance matrix $S$ with the Floyd algorithm [37]. The traditional search algorithm is only suitable for route planning of static traffic network models, i.e. to solve optimal routing one time before the departure of EVs. It means that the route does not change with the real-time information of traffic networks. Thus, the congested road sections due to changes in traffic network conditions cannot be avoided in the actual driving route, causing the routing planned by the traditional search algorithm not to be optimal in dynamic traffic networks.

*2) Solution*: To solve optimal routing planning in dynamic traffic networks, a receding-horizon based optimal routing method is proposed, whose specific steps are shown in Fig.4.

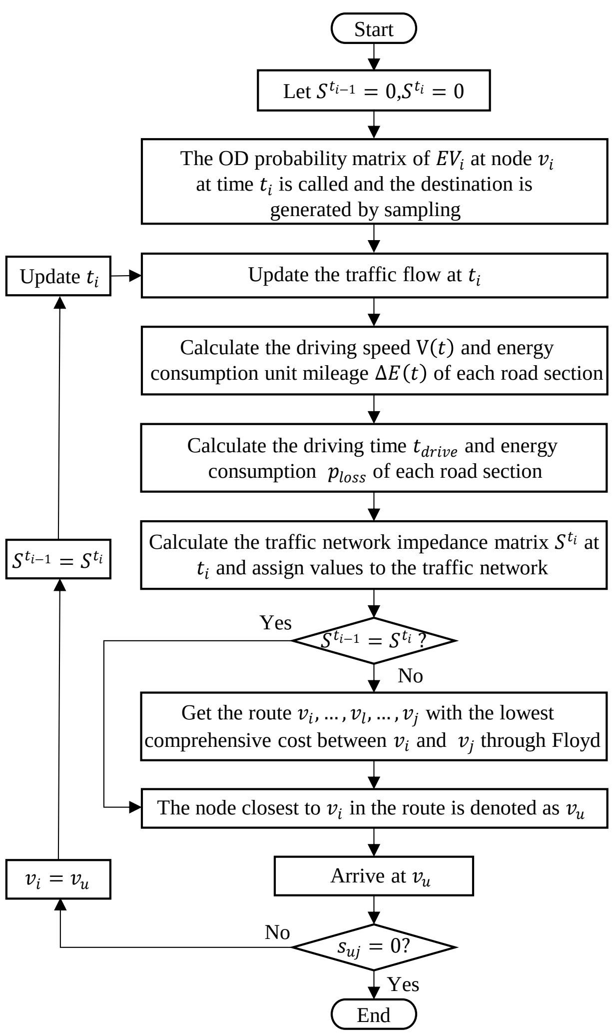


Fig. 4. Receding-horizon based optimal routing method

As seen from Fig.4, starting from origin $v_i$, at each time the EV reaches the next traffic network node $v_u$, the traffic network impedance matrix $S^{t_i}$ at time $t_i$ is recalculated. Then, it is to determine whether the new impedance matrix $S^{t_i}$ is the same as the previous impedance matrix $S^{t_{i-1}}$. If yes, the EV continues to drive according to the previous driving routing; otherwise, the Floyd algorithm is called to search for a new route, and the EV will follow the new route.

Then, the routing formed by all driving nodes is the optimal routing.

$$l_{ij} = \{v_i, \dots, v_a, \dots, v_j\} \tag{13}$$

### B. Dynamic Charging Service Pricing Strategy

*1)Problem Description*: In real situations, the user's decision on where to charge is independent and "selfish", without any consideration of the operation of charging stations, traffic networks and power grids, etc. This large-scale disorderly EV charging will cause serious congestions at charging stations in urban core areas, which further increases the burden on the regional power grid. Simultaneously, the utilization rate of charging stations in non-urban core areas is very low, making charging facilities not effectively used.

*2) Solution*: To address the imbalance caused by the large-scale disorderly EV charging, a charging service pricing strategy is proposed. The charging service fee is adjusted dynamically through the occurrence of events that EVs request for charging, arrive, or leave charging stations to guide EVs to underutilized charging stations, realizing the spatial transfer of charging demand load.

$$p_{s,k}(t_r) = \begin{cases} p_{s,0} & 0 \le C_k(t_r) + Q_k(t_r) < \frac{1}{\beta} G_k \\ \beta p_{s,0} \frac{C_k(t_r)+Q_k(t_r)}{G_k} & \frac{1}{\beta} G_k \le C_k(t_r) + Q_k(t_r) < G_k \\ \beta p_{s,0} + \frac{\delta t_w}{E_{ex}-E_{re}} & G_k \le C_k(t_r) + Q_k(t_r) \end{cases} \tag{14}$$

where $p_{s,0}$ is the basic service fee of charging station $k$ which is denoted as $CS_k$, $t_r$ is time that EV requests for charging, $C_k(t_r)$ is the actual number of EVs in $CS_k$ at $t_r$, including queue $C_{k,c}(t_r)$ being charged and queue $C_{k,w}(t_r)$ being queued, $Q_k(t_r)$ is the reservation queue of $CS_k$, indicating the EVs that has already reserved for charging at $CS_k$ but has not yet arrived, $G_k$ is the number of the charger in $CS_k$, $\delta$ is the waiting unit time cost coefficient, $E_{ex}$ is the electric quantity of EV after charging, $E_{re}$ is the remaining power when EV arrives at the $CS_k$,and $t_w$ is the waiting time of EV in $CS_k$.

It can be seen from (14) that, when events that EVs request for charging, arrive or leave $CS_k$ occur, the queue $Q_k(t_r)$, $C_{k,w}(t_r)$ and $C_{k,c}(t_r)$ will change, which in turn changes charging service fees. In this pricing strategy, the charging service fee provided by charging stations with lower charging demand is lower than those with higher charging demand. This price difference will incentivise EVs to move from crowded charging stations to underutilized charging stations for charging.

Besides, the charging service fee of an EV is only related to charging station charging demand when the EV requests for charging. It is not affected by the factors after the request, which ensures the timeliness of the EV's charging reservation. The charging choice of EV will change the reservation queue and the service fee of the corresponding charging station. This then affects the charging choices of EVs that subsequently request for charging, reflecting the interactive impact between EVs charging strategies.

### C. Charging Navigation Model

The charging navigation strategy proposed in this paper is particulalry suitable for guiding EVs with fast charging requirements to the charging station for energy replenishment. The conventional charging mode of EV (i.e. low-power charging) and electric buses with fixed driving routing is not within the scope of discussion. In this section, the modeling and analysis of a single EV are firstly carried out according to its charging characteristics. Then the charging decision function is established for charging navigation of EVs to minimize the total cost. Finally, based on all modeling and analysis, the flowchart of the route planning and charging navigation for EVs is given.

*1) Charging Model of Single EV*: The travel destination of an EV at each time of the day can be obtained through OD analysis [36]. Assuming that at $t_i$, there is an EV denoted as $EV_i$ at node $v_i$. The destination $v_j$ of $EV_i$ for the next travel can be obtained by OD probability matrix sampling.

Before starting the next travel, whether the $EV_i$ needs charging can be determined through:

$$E_i(t) \le \gamma E_{bat} \quad or \quad E_i(t) \le l_{ij}\Delta E(t) \tag{15}$$

where $E_i(t)$ is the remaining power of $EV_i$ at time $t$, $E_{bat}$ is the battery capacity, $\gamma$ is mileage anxiety coefficient, $\Delta E(t)$ is energy consumption unit mileage.

If the operating state of the $EV_i$ does not meet (15), $EV_i$ drives to destination $v_j$ according to the dynamic routing planning model described; if it meets (15), the $EV_i$ charging request flag $C_r(i)$ will be triggered, and then the intelligent navigation system plans the charging strategy for $EV_i$.

$$C_r(i) = \begin{cases} 1 & E_i(t) \le \gamma E_{bat} \ \ or \ \ \ E_i(t) \le l_{ij}\Delta E(t) \\ 0 & E_i(t) > \gamma E_{bat} \ \ and \ \ E_i(t) > l_{ij}\Delta E(t) \end{cases} \tag{16}$$

During the travel of $EV_i$, driving time, driving distance, and charging cost are all factors that users are concerned with. These factors are uniformly converted into the cost, and the charging strategy is planned to minimize the total charging cost of EV drivers.

Record the time when $EV_i$ requests charging as $t_r$, then the charging price of the $EV_i$ at $CS_k$ is:

$$p_k(t_r) = p_0(t_r) + p_{s,k}(t_r) \tag{17}$$

where $p_0(t_r)$ is the real-time electricity price of the power grid at $t_r$.

The remaining power of $EV_i$ when it reaches $CS_k$ is:

$$E_{re,i,k} = E_i(t_r) - l_{ij}\Delta E_t \tag{18}$$

where $E_i(t_r)$ is the remaining power of $EV_i$ at $t_r$ .

The time of the $EV_i$ arriving at $CS_k$ is:

$$t_a = t_r + \frac{l_{ij}}{\bar{V}_t} \tag{19}$$

The charging time of $E_i(t_r)$ at $CS_k$ is:

$$t_c = \frac{E_{ex,i,k} - E_{re,i,k}}{P\varepsilon} \tag{20}$$

where $P$ is the power of charger, $\varepsilon$ is charging efficiency.

The waiting time of the $EV_i$ at the $CS_k$ depends on the sum of the electric power demand of EVs charging and queuing before the $EV_i$. The queuing time varies with the dynamic queue of $CS_k$, which can be solved by the steps in Fig.5.

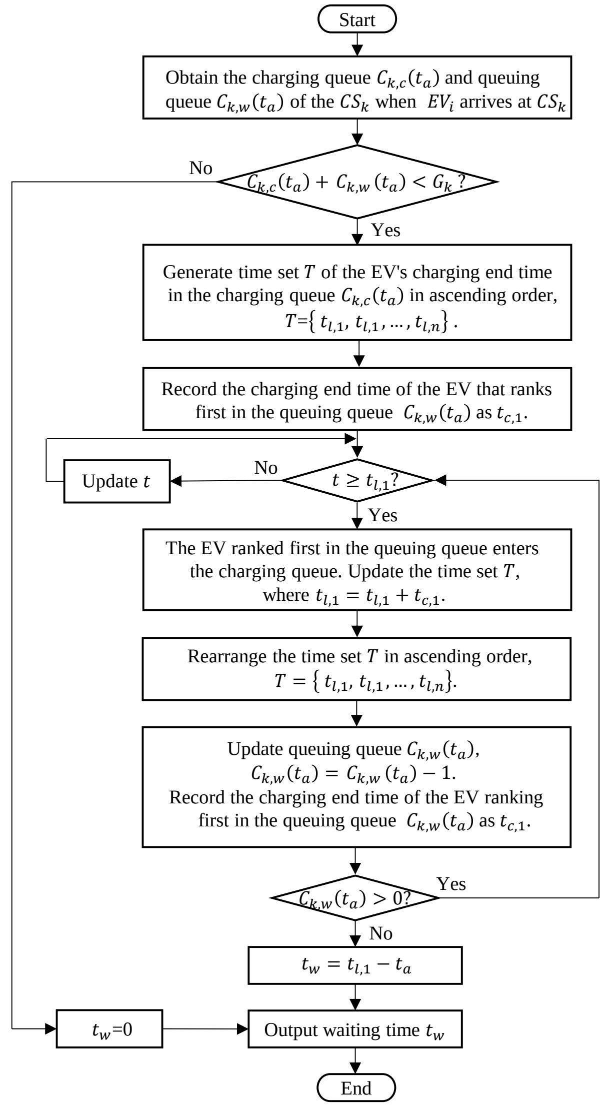


Fig. 5. Flowchart for computing the waiting time

The time $EV_i$ departure from $CS_k$ is:

$$t_l = t_w + t_a + t_c \tag{21}$$

The charging expense of $EV_i$ at $CS_k$ is:

$$C_{i,k} = \left(E_{ex,i,k} - E_{re,i,k}\right)p_k(t_r) \tag{22}$$

The total cost of $EV_i$'s charging strategy includes not only the charging expense but also the driving cost from the origin $v_i$ to the $CS_k$ and from $CS_k$ to the destination $v_j$. The total cost is:

$$C_{all,i,k} = \sum_{i=1}^{n}\sum_{\substack{j=1\\ i\neq j}}^{n} s_{ij}^{ok}\, x_{ij} + \sum_{i=1}^{n}\sum_{\substack{j=1\\ i\neq j}}^{n} s_{ij}^{kd}\, x_{ij} + C_{i,k} \tag{23}$$

where $n$ is the total number of the traffic network node, $s_{ij}^{ok}$, $s_{ij}^{kd}$ represents the impedances of the road section with $i$ and $j$ as both endpoints from the origin to the $CS_k$ and from the $CS_k$ to the destination respectively, $x_{ij}$ is the 0-1 variable, if the road with $i$, $j$ as the endpoint is in the actual driving route, $x_{ij} = 1$, otherwise $x_{ij} = 0$.

The $CS_k$ is the centralized load of the 10kV distribution network. For the distribution network node where $CS_k$ is located, the total charging load $P_k$ in any period is the accumulation of the charging power of EVs charged in $CS_k$.

$$P_k = \sum_{i=1}^{\tilde{n}} P_{i,t} \tag{24}$$

where $\tilde{n}$ is the total number of EVs in period $t$, $P_{i,t}$ is the charging power of $EV_i$ in period $t$.

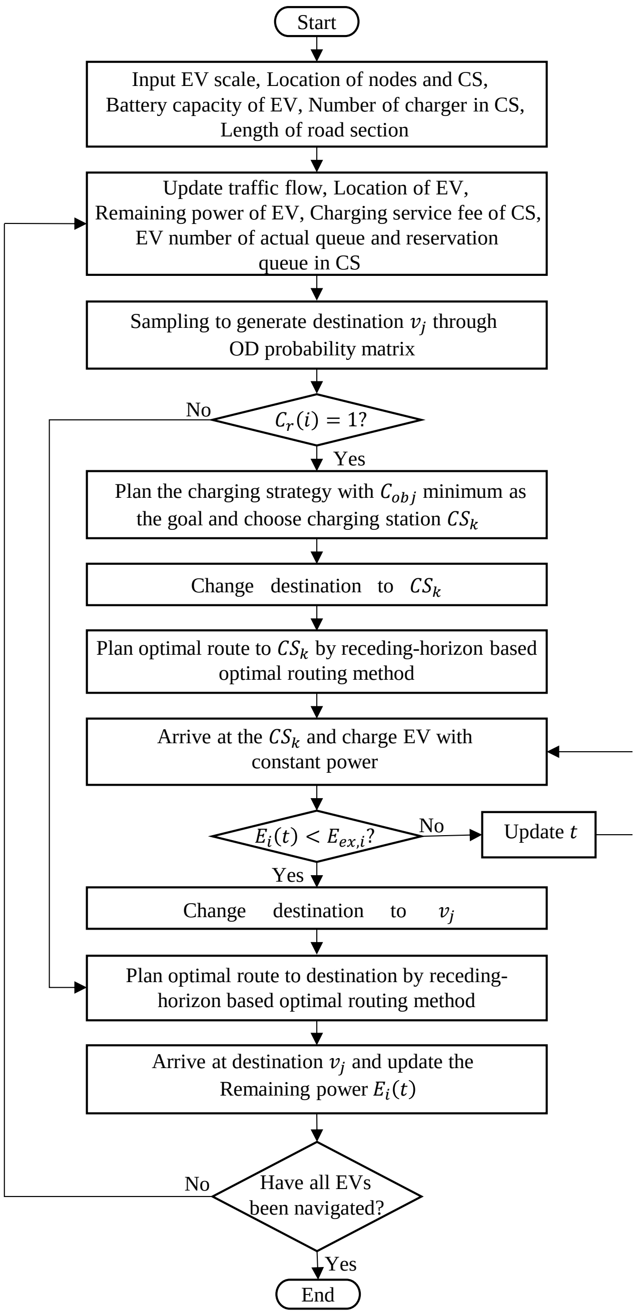


Fig. 6. Flowchart of the route planning and charging navigation

*2) Charging Decision Function*: With the lowest total cost as the objective to plan the optimal charging strategy for users, the charging decision function proposed is as follows, with the constraint of the waiting time tolerance, remaining mileage coverage, and driving speed

$$C_{obj} = min\{C_{all,i,1}, \dots, C_{all,i,k}, \dots, C_{all,i,z}\} \tag{25}$$

$$s.t. \qquad E_i(t_r) \geq l_{ok} \Delta E(t) \tag{26}$$

$$\bar{V}_{ij}(t) \geq \lambda \bar{V}_{ij-z} \tag{27}$$

$$t_{w,obj} \leq \mu t_{w,close} \tag{28}$$

where $C_{all,i,k}$ is the total cost, $l_{ok}$ is the optimal route from the origin to $CS_k$, $t_{w,obj}$ and $t_{w,close}$ is the waiting time at the target charging station and the nearest charging station respectively.

Constraint (26) limits the target charging station to be within the remaining mileage of $EV_i$. Constraint (27) is to avoid congested roads, limiting the speed of recommended road sections. Constraint (28) is to avoid the congestion of some charging stations due to a large number of EV charging reservations.

Based on the foregoing modeling and method analysis, Fig.6 shows the flowchart of the routing planning and charging navigation of EVs.

### D. Priority Reservation Cost Mechanism

*1)Problem Description*: In the above discussion on the charging service pricing strategies, it is assumed the reservation time of each EV is in order. However, in real situations, sometimes multiple EVs request for charging simultaneously particularly during peak hours. It has rarely been studied regarding how to deal with the reservation sequence of these EVs that request for charging simultaneously.

*2) Solution*: To solve the problem, a priority reservation cost mechanism is proposed. Suppose that at time $t_r$, $M$ EVs, denoted as $EV_1, EV_2, \dots, EV_i, \dots, EV_m$, simultaneously request for charging.

For $EV_i$, the charging stations which is within its remaining mileage, are all its possible charging choices. The estimated arrival time of $EV_i$ at $CS_k$ is:

$$t_{a,i,k} = t_r + \frac{L_k}{\bar{V}(t)} \qquad k \in [1.7] \tag{29}$$

The time set of all EV's estimated arrival time is:

$$T = \{\dots, t_{a,1,k}, \dots, t_{a,i,k}, \dots, t_{a,m,k}\} \quad k = 1,2, \dots, 7 \tag{30}$$

For $CS_k$, it may be within the remaining mileage of more than one EVs among these $M$ EVs. According to the order in which these EVs arrive at $CS_k$, the estimated reservation queue $Q_k$ of $CS_k$ is generated.

$$Q_k = \{EV_i, \dots, EV_j, \dots EV_e\}$$
$$i, j, e \in [1, m] \quad k = 1,2, \dots, 7 \tag{31}$$

Record the smallest $t_i$ in $T$ as $t_{min}$. Record the charging station and EV corresponding to $t_{min}$ as $CS_{r1}$, $EV_{r1}$. $EV_{r1}$ is assumed to have priority reservation opportunity in these $M$ EVs.

As seen from (14), the charging service fee is determined by the queue $C_k(t_r)$, $Q_k(t_r)$ of the charging station when the EV requests for charging. With this pricing strategy, $CS_{r1}$ is the fastest arriving charging station for $EV_{r1}$, but it is not necessarily the one with the lowest comprehensive charging cost. The navigation of the charging station for $EV_{r1}$ needs to be further determined.

By assuming the reservation queue of $CS_k$ to be $Q_k$, it can be written as:

$$Q_k = \{EV_i, \dots, EV_{r1}, \dots EV_e\} \quad i, e \in [1, m] \tag{32}$$

In $Q_k$, record the queue before $EV_{r1}$ as $Q_{bk}$, and the queue after $EV_{r1}$ as $Q_{ak}$. The charging service fee of $EV_{r1}$ at $CS_k$ is:

$$p_{s,k}(t_r) = \begin{cases} p_{s,0} & 0 \le C_k(t_r) + Q_k(t_r) + Q_{bk} < \frac{1}{\beta} G_k \\ \beta p_{s,0} \frac{C_s(t_r) + Q_s(t_r) + Q_{bk}}{G_k} & \frac{1}{\beta} G_k \le C_k(t_r) + Q_k(t_r) + Q_{bk} < G_k \\ \beta p_{s,0} + \frac{\delta t_{w'}}{E_{ex} - E_{re}} & G_k \le C_k(t_r) + Q_k(t_r) + Q_{bk} \end{cases} \quad (33)$$

The comprehensive charging cost of $EV_{r1}$ at $CS_k$ is:

$$C_{all,r1,k} = \sum_{i=1}^{n} \sum_{\substack{j=1 \\ i \neq j}}^{n} s_{ij}^{ok} x_{ij} + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ i \neq j}}^{n} s_{ij}^{kd} x_{ij} + \left(E_{ex,r1,k} - E_{re,r1,k}\right)\left(p_{s,k}(t_r) + p_0(t_r)\right) \quad (34)$$

Compared with (23), there is an extra cost in $C_{all,r1,k}$ caused by $Q_{bk}$, which is denoted as a priority reservation cost in this paper. It is the extra cost for $EV_{r1}$ to pay for reserve charging before EVs that is the queue $Q_{bk}$. If $Q_{bk}$ is 0, it means that $EV_{r1}$ is at the top of the queue $Q_k$. After considering the priority reservation cost, the $CS_k$ with the lowest comprehensive charging cost is the final choice of $EV_{r1}$.

$$C_{all,r1,i} = min\{C_{all,r1,k}\} \quad k = 1,2,\dots,g \quad (35)$$

where g is the number of charging station, which is located within the remaining mileage of $E_{r1}$.

Increase the number of EVs in the reservation queue $Q_i(t_r)$ of $CS_i$ by (36):

$$Q_i(t_r) = Q_i(t_r) + 1 \quad (36)$$

By repeating above process, the reservation orders and charging choices of the $M$ EVs can be obtained in turn.

## V. CASE STUDY

In this section, simulation results are presented to demonstrate the performance of the proposed method. The traffic network topology and other parameters used in the simulation are given in Section V.A. The effects of navigation strategies on the queue, charging load, charging price and service rate of charging stations are analyzed.

### A. Case Description

The numerical cases for an urban city is modelled to verify the feasibility of the route planning and charging navigation strategy. According to traffic functions, the urban city is divided into: residential area (nodes of 2-3-4-9-8-14-13-7 and nodes of 28-29-34-33-32), commercial area (nodes of 14-15-16-23-22-21-18), working area (nodes of 9-10-11-16-15 and nodes of 20-21-27-26). The urban city contains 7 charging stations, which are denoted as cs1,cs2,…,cs7. The traffic network topology and charging station locations are shown in Fig.7.

A total of 1800 identical BYD Qin ev450 are used as simulations, whose battery capacity is 60 kWh [38]. Considering that the charging mode in this paper is all in the fast charging situation, the charging power $P$ [39] and the charging efficiency $\varepsilon$ [14] of the charger are uniformly set as 90kW and 0.9 respectively. To avoid damage to the battery caused by overcharging, $E_{ex}$ is set to 0.9 $E_{bat}$ after charging [40]. Referring to [41], $\theta$ is set to 0.39. Referring to the test data of reference [32], $a$ , $b$, $n$ in (3), (4) is set to 1.726, 3.15, 3 in the urban expressway. For main roads and secondary roads, $a$ , $b$, $n$ is set as 2.076, 2.870, 3, respectively. Referring to [44], $p_{s,0}$ is set as 0.8 Yuans, while $p_0$ is:

$$p_0 = \begin{cases} 1.0044 \quad Yuan/kWh & T \in (10{:}00,15{:}00) \cup (18{:}00,21{:}00) \\ 0.6950 \quad Yuan/kWh & T \in (07{:}00,10{:}00) \cup (15{:}00,18{:}00) \cup (21{:}00,23{:}00) \\ 0.3946 \quad Yuan/kWh & T \in (23{:}00,07{:}00) \end{cases} \quad (37)$$

Besides $\gamma$, $\beta$, $\mu$, $\lambda$, $\delta$ are set as 0.15, 2, 2.5, 0.3, 0.18 respectively according to the model in this paper.

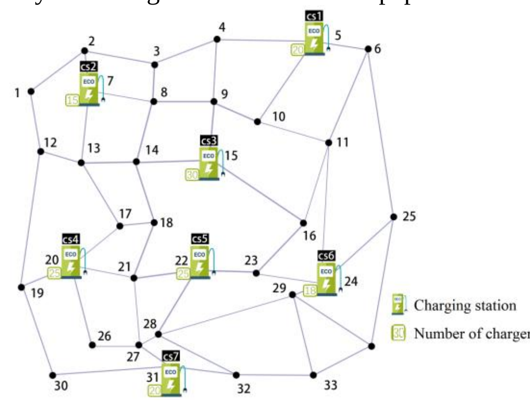


Fig. 7. Traffic network topology

### B. Discussion

In this section, the simulation results are analyzed from different aspects to verify the effectiveness of the proposed method, which cannot only alleviate difficulty for EV's fast charging but also improve the utilization rate of charging facilities.

This program runs on ThinkPad notebooks configured as i5-6200u and 16gm and the simulation platform is MATLAB. The simulation time of a single time interval is 3.13 s.

*1)Analysis of changing demand distribution:* Without routing and charging navigation, the EV users choose the nearest driving route and charging station during daily driving. The distribution of EV's charging demand without navigation for the whole day in the traffic network is displayed in Fig.8. The peak time of EV's charging demand is 13:00-16:00, which is between the morning and evening travel peaks of users. Besides, the charging demand is unevenly distributed in space, mainly concentrated in the area where the traffic network node 10 to node 20 are located. To show this more clearly, the charging demand of each road section in the peak period is given in Fig.9. As can be seen, the charging demand is mainly concentrated in the working area and the commercial area as well as its adjacent road sections, which makes cs3, cs4, cs5 may face greater charging pressure during peak hours, but cs1, cs6, cs7 are not fully used. The service situation of each charging station at 15:00 is shown in Fig.10. It's obvious that, the number of EVs in the actual queue and reservation queue at cs3, cs4, cs5 has exceeded it's service capacity cap, especially at cs3, which has exceeded twice it's service capacity cap.

Simulation results in Figs.8-10 demonstrate that the distribution of EV's charging demands without navigation is unbalanced. This unbalanced distribution will lead to the two concerns mentioned in the first Section, i.e. the difficulty of fast charging for EVs and the inefficient use of charging infrastructures.

*2)Analysis of different routing strategies:* To illustrate the advantage of the receding-horizon based optimal routing method in routing planning over the traditional search algorithm, the driving route of an EV with node 2 as the origin and node 22 as the destination with different strategies is showed in Fig.11.

In Fig.11, routing 1 is the shortest route, and routing 2 , routing 3 are the driving routes obtained by the traditional search algorithm and the receding-horizon based algorithm. Routing 1, routing 2, and routing 3 are marked on the traffic network with orange, red, and green lines respectively. Besides, the traffic condition of the road sections when EV driving on it is represented by some composite colour on the basis of orange, red and green. Pure orange, pure red, pure green represent the road section is unblocked. green black, orange black, red black and black green, black orange, black red represent the road section is crawl and blocked respectively. Combined with the information in Table.1, routing 1 has the shortest distance among the three routings, which is 16.07 km. However, compared with routing 2 and routing 3 obtained by the comprehensive road impedance model, the driving time 26.137 min and driving cost 15.12 yuans of routing 1 are the most among the three routings. The reason is that the traffic condition of each section will not be taken into account when planning the driving route with the shortest distance, which will cause some congested road sections to be planned into the driving routing.

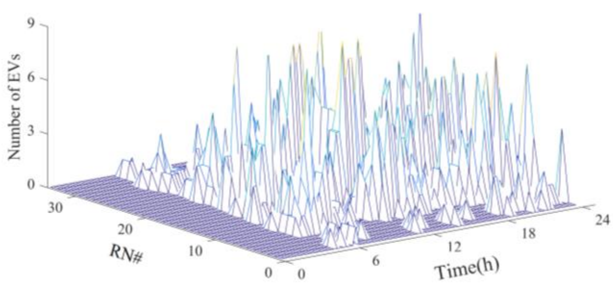


Fig. 8. Spatiotemporal distribution of charging demand

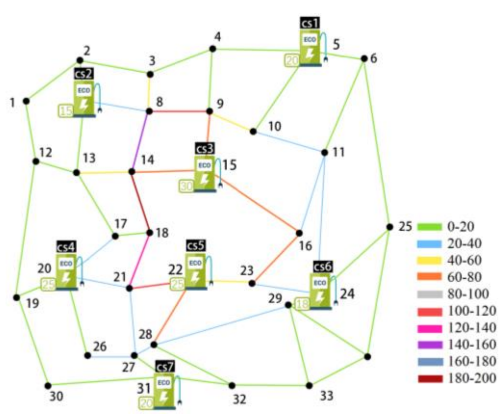


Fig. 9. Network distribution of charging demand

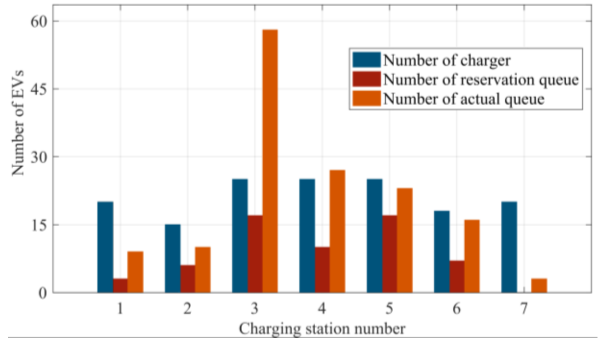


Fig. 10. The actual number and reservation number of EV

To further analyze the difference between routing 2 and routing 3, it can be seen that although routing 3 is longer routing 2, the driving time and driving cost are reduced. It's easy to understand, because routing 2 is planned by the traditional search algorithm one time according to traffic network information before the departure of the EV, which means that routing 2 does not change with the real-time information of traffic network. Thus, the congested road sections due to changes in traffic network condition cannot be avoided.

The shortcomings of traditional search algorithm can be solved by the receding-horizon based optimal routing algorithm proposed. As shown in Fig.11, when the EV arrives at node 13, $s_{13-17-18-21-22}$ obtained by the receding-horizon based optimal routing algorithm is less than $s_{13-14-18-21-22}$ due to the change in traffic condition. EV will adjust the driving routing from routing $l_{13-17-18-21-22}$ to the destination instead of routing $l_{13-14-18-21-22}$. As listed in Table.1, the driving time and driving cost is further reduced to 21.933 min and 11.79 yuans.

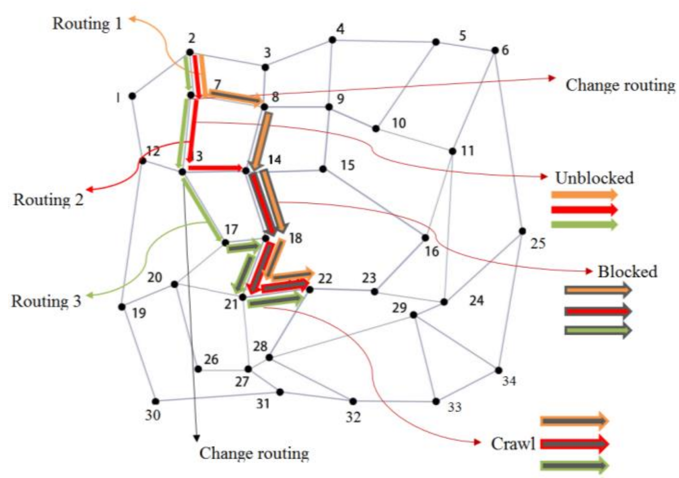


Fig. 11. Routing of $EV_i$ in different strategies.

TABLE I.
INFORMATION OF ROUTING

| Routing | Actual Route | Dis(km) | Time(min) | Cost(yuans) |
|---|---|---|---|---|
| 1 | 2-7-8-14-18-21-22 | 16.07 | 26.137 | 15.12 |
| 2 | 2-7-13-14-18-21-22 | 16.41 | 22.853 | 12.54 |
| 3 | 2-7-13-17-18-21-22 | 16.45 | 21.933 | 11.79 |

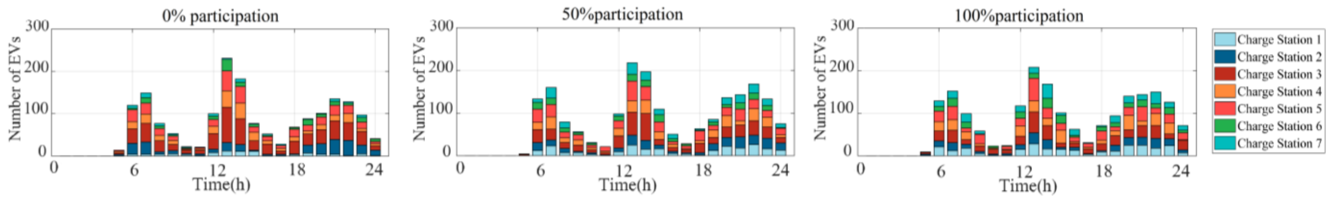

Fig. 12. Number of EVs in reservation queue at each charging station in different user participation levels

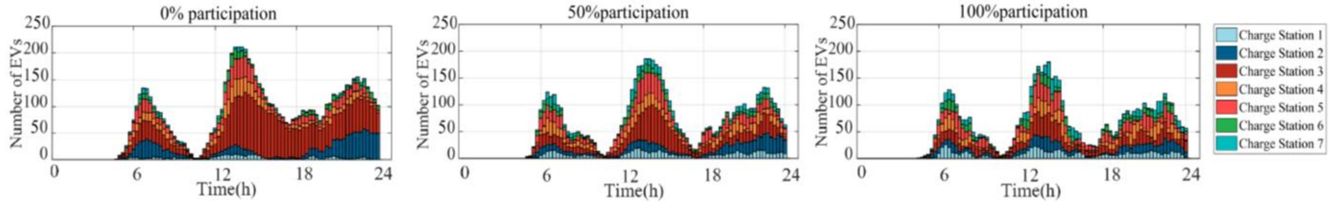

Fig. 13. Number of EVs in actual queue at each charging station in different user participation levels

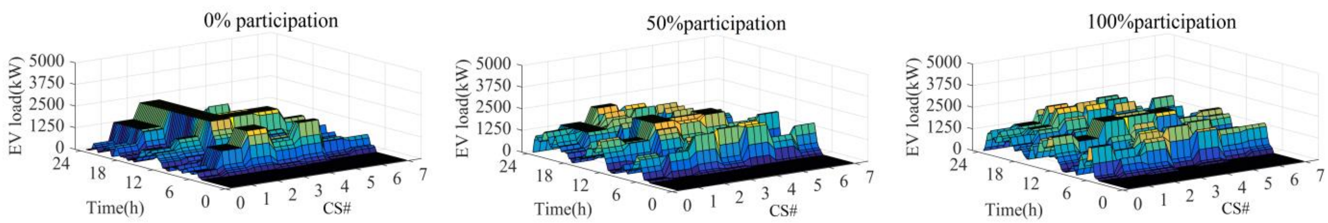

Fig. 14. Charging load of charging station in different user participation levels

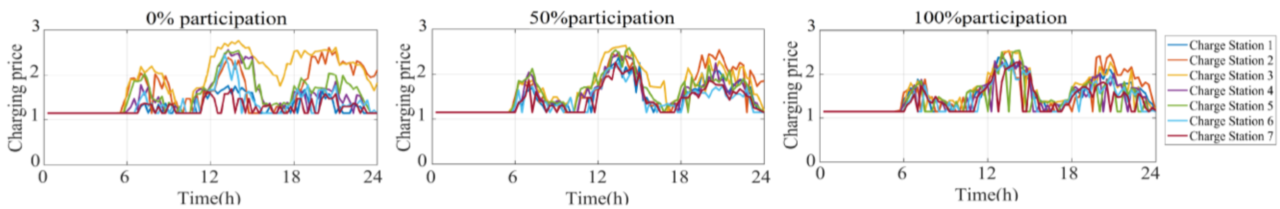

Fig. 15. Charging price of charging station in different user participation levels

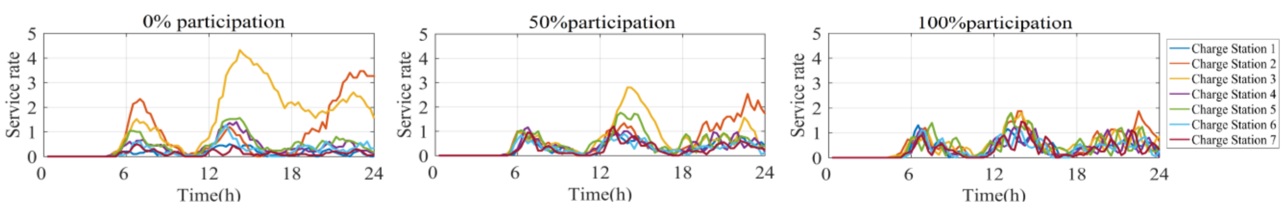

Fig. 16. Service rate of charging station in different user participation level

*3)Analysis of charging strategy*: To verify the effectiveness of the proposed charging strategy, simulation results with three different user participation degrees, 0% acceptance, 50% acceptance, and 100% acceptance, are presented. EV users, who do not accept charging navigation, choose the nearest charging station.

The number of EVs in the reservation queue and actual queue at each charging station with three user participation levels is displayed in Fig.12-13. As can be seen from the scenario of 0% user participation, the number of EVs reserved for charging in cs3 accounts for the majority of EVs with charging demand, which leads to the result that cs3 will face the number of EVs far exceeding the upper limit of it's charging service capacity. With the increasing user participation, the EVs that originally choose cs3 turn to other charging stations for charging. As the result, more EVs can receive charging services instead of queuing at cs3, which not only relieves the charging pressure of charging stations in the central area but also improves the utilization rate of remote charging stations.

To analyze the impact of charging behavior on the distribution network, the EV's charging load of each charging station is showed in Fig.14. Compared with three subgraphs with different participation, it can be seen that with 0% participation, the charging load distribution of each charging station is unbalanced, making the peak-valley difference among stations larger. With increasing participation, the peak-to-valley difference of the maximum load is reduced from 2520kW to 1350kW. The results show that the peak-valley difference of the charging load among charging stations is reduced, which is beneficial to the operation of charging stations.

It can be seen from (14) that the charging service fee is related to the charging demand of the charging station. The change in charging demand will be directly reflected in the charging price. The charging price curve of each charging station is displayed in Fig.15. The charging price difference between different charging stations is very large in the scenario of 0% user participation. The charging price of cs3 during peak hours is close to 3 yuans, while that of cs7 all day is less than 1.8 yuans. With increasing participation, this price difference among charging stations tends to decrease and even disappears in some periods, which means a more balanced distribution of charging demand.

To further explain the utilization rate of each charging station in a day, the service rate is introduced as the evaluation index.

$$S_r(t) = \frac{C_k(t)}{G_k} \tag{38}$$

$S_r(t) = 1$ indicates the ideal running state of the charging station, which means that the charger is fully used and there are no queued EVs. The more $S_r(t)$ is greater than 1, the more congested the charging station is; The more $S_r(t)$is smaller than 1, the lower the utilization of the charging station is.

The service rate curve of the charging station is displayed in Fig.16. As can be seen, in the scenario of 0% user participation, the service rate of cs3 has exceeded 1 from time 12, especially the service rate at time 14 is as high as 4. Meanwhile, the service rate of cs1 and cs7 are both lower than 0.5 throughout the day. It shows that the distribution of charging services between charging stations is very unreasonable. In contrast, the charging service rate of charging stations is closer to 1 along with the increase in user participation, which means more rational operation state of charging station.

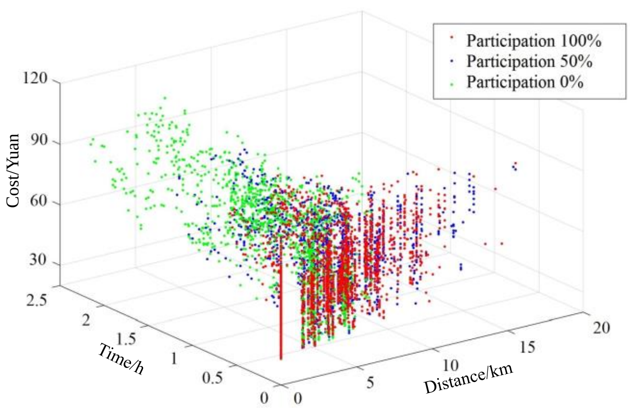


Fig. 17. Distribution of EV in three participation levels

TABLE II.
CHARGING DEMAND FREQUENCE

| Node | Number | Number | Node | Node | Number |
|---|---|---|---|---|---|
| 1 | 5 | 13 | 27 | 24 | 30 |
| 2 | 20 | 14 | 230 | 25 | 2 |
| 3 | 74 | 15 | 118 | 26 | 35 |
| 4 | 17 | 16 | 125 | 27 | 40 |
| 5 | 2 | 17 | 17 | 28 | 58 |
| 6 | 1 | 18 | 222 | 29 | 30 |
| 7 | 41 | 9 | 4 | 30 | 2 |
| 8 | 162 | 20 | 40 | 31 | 8 |
| 9 | 156 | 21 | 152 | 32 | 24 |
| 10 | 54 | 22 | 121 | 33 | 14 |
| 11 | 56 | 23 | 55 | 34 | 11 |
| 12 | 5 | | | | |

The distribution of EV driving distance, charging cost, and charging time of users with different participation levels is shown in Fig.17. Compared with the scenario of 0% participation, although the average charging distance increases from 3.13 km to 4.75 km, the charging time and charging cost reduces from 68.93 min to 40.32 min, 70.91 yuans to 64.96 yuans, respectively. It shows that compared with the charging strategy without navigation, the charging strategy under navigation can better satisfy the charging demands of users.

Finally, based on the charging demand distribution with the scenario of 100% user participation, the locations of new charging stations are planned. After 50 simulations, Table.2 gives the charging demand frequency of each traffic network node in one day. Combined with the research on the location planning of the charging station [26-28], node 14 and node 18 are selected as the new charging station locations, as shown in Fig.18. The information comparison of EV charging strategy in different scenarios is displayed in Table.3. For more directly illustrate it, the relative values of average charging distance, charging time, and charging expense of users with different scenarios are shown in Fig.19, in which the value of 0% participation is taken as the base.

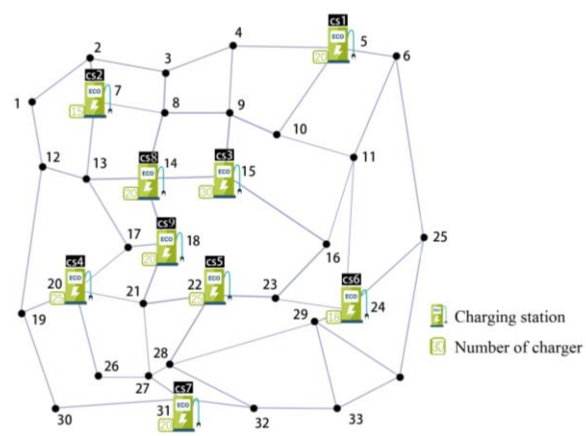


Fig. 18. Traffic network topology with new charging stations

TABLE III.
TABLE IV. CHARGING STRATEGY INFORMATION

| Scenarios | Distance(km) | Time(min) | Cost(yuans) |
|---|---|---|---|
| 0% acceptance | 3.13 | 68.93 | 70.91 |
| 50% acceptance | 4.16 | 42.65 | 68.06 |
| 100% acceptance | 4.75 | 40.32 | 64.96 |
| 100% acceptance with new charging station | 3.56 | 37.23 | 62.60 |

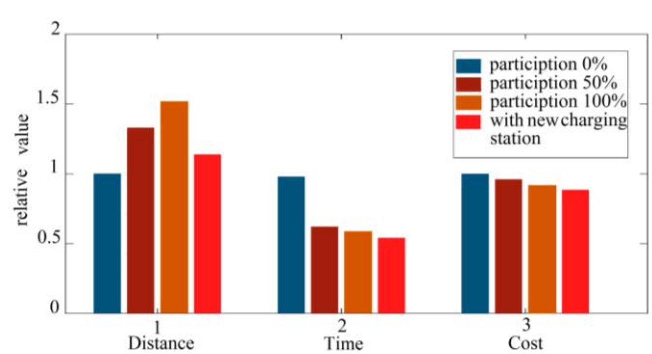

Fig. 19. Information on charging strategy in different scenarios

The results show that after the new charging station is added, the average charging distance, charging expense, and charging time is further reduced. They prove that it is reasonable to plan the location of charging stations based on the EV's charging demand distribution with the navigation strategy.

## VI. Conclusion

To solve the problem of EV fast charging on the road and the unbalanced utilization of charging infrastructures, a routing optimization of EVs for charging with an event-driven pricing strategy is proposed. Taking the numerical analysis of an urban area as an example, the effectiveness of the proposed strategy is verified by simulation results, which show that:

1) Compared with the static shortcoming of the traditional search algorithm, the receding-horizon based optimal routing algorithm can recommend the optimal routing according to the real-time information of the traffic network. It can not only be used as the navigation algorithm to plan the driving route but can also search for the optimal charging strategy by comprehensive cost road impedance.
2) The dynamic service pricing strategy proposed can reflect the congestion of charging stations, which lays the foundation for developing charging navigation strategies.
3) With the integration of real-time traffic information and charging station information, the routing planning and charging navigation strategy can reasonably control the number of EVs in each charging station. This can shorten the queuing time of EVs into the station while improving the safety of charging station operation.
4) After the new charging stations are planned in the traffic network, the charging time and charging cost further is reduced by 7.66%, 3.63% respectively, which verifies the rationality to plan the charging station location based on the distribution of EV charging demand with the navigation strategy. It provides a theoretical basis for further research on the planning of the charging station location.

Considering the effects of various time-varying external factors on EV's charging cost, the method proposed in this paper plan the routing and charging strategy for users. However, different types of EV users have their own personalized needs about travel behaviors. The study on the user's charging habit and routing choice preference in multiple scenarios is not covered in this article, which will be further explored for meeting the personalized needs of EV drivers in the follow-up research.

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